From Images to Insight: Clinical Decision Support Systems (CDSSs) in Oral and Maxillofacial Radiology

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ABSTRACT

The clinician's preliminary diagnosis and the pathologist's conclusive histopathological diagnosis, which is considered the gold standard, are not always the same. Due to time constraints and the high volume of patients, clinicians often rely on initial impressions or memorable experiences, which can potentially lead to diagnostic inaccuracies.

Artificial Intelligence (AI), with its data-driven approach, offers a more objective analysis free from personal biases. Clinical Decision Support Systems (CDSSs), combine demographic, clinical, and radiological data, to generate differential diagnoses, providing clinicians with additional decision support. This, in turn, increases the efficiency and accuracy of clinical diagnoses. CDSSs have demonstrated high accuracy rates in internal medicine, especially when diagnosing common chief complaints.

Bayesian Belief Networks (BBNs) are applied in both medical and dental fields to enhance diagnostic accuracy. An example is the Oral Radiographic Differential Diagnosis (ORADIII) system developed by the University of California, Los Angeles (UCLA) in the 1990s, which employs the Bayesian approach to diagnose intra-bony lesions of the jaw. Using AI in decision support for diagnosing bony jaw lesions (including cysts and tumors) lies in its potential to aid in improving clinician's diagnostic accuracy, efficiency, and consistency. AI can further help with complex diagnoses, reduce diagnostic errors, provide support in high-volume or remote settings, as well as work educational tool for students.

KEY WORDS

Artificial intelligence, Clinical decision support systems, Diagnostic imaging, Jaw diseases

INTRODUCTION

With the coming age, integration of Artificial Intelligence is seen in almost all aspects of life, even the medical field, especially the field of radiology. Clinical Decision Support Systems (CDSSs) like ORADIII and ORAD DDx are available to help diagnose oral intra bony lesions.

Other than clinical, three approaches exist to developing a differential diagnosis or confirming a diagnosis. They are radiological, pathologic, or surgical approaches. Imaging features of a central lesion, based on principles of interpretation, are used for radio-diagnosis and its differential, by Oral and maxillofacial (OMF) radiologists, who comprise a subspecialty of dentistry. It requires systematic analysis and categorization of lesions based on various features.[1]

Step 1: Localize Abnormality

Step 2: Assess Periphery and Shape

Step 3: Analyze Internal Structure

Step 4: Analyze Effects of Lesion on Surrounding Structures

Step 5: Formulate Interpretation

IMPORTANCE OF ACCURATE DIAGNOSIS FOR TREATMENT PLANNING AND PROGNOSIS

Imaging features of multiple lesions within the jaws resemble each other and are not always unique and distinct from their pathology. This somewhat puts the radio-diagnosis under the radar.[2]

Pathology gives a diagnosis based on the tissue of origin and changes seen at that level, thereby making biopsy a more reliable method and the gold standard for the diagnosis of many jaw lesions.[3]

ROLE OF HISTOPATHOLOGICAL EXAMINATION

a. Diagnosis of lesions with variant imaging features as per its stage: Some lesions, for example, Eosinophilic Granuloma, show imaging features based on the stage of the lesion. Starting as a radiolucent lesion, with ill-defined borders to well-defined, and in the final stage, it presents with sclerotic borders. This makes diagnosis based on radiographic features as not very reliable.[4]

b. Diagnosis of lesions with resembling imaging features: Dentigerous cyst and Odontogenic Keratocyst, both present radio graphically as unilocular, well-defined radiolucency containing a tooth. This description is not enough for the operating surgeon since the pathology and management of both entities are different. The former being benign while the latter is known for its high recurrence rate.[5]

c. Differentiate benign from malignant lesions: Histopathology picture helps to differentiate benign from malignant

d. Aid in Treatment planning: With the accurate and confirmed diagnosis, an appropriate treatment plan can be formulated.

In spite of the above advantages, there are certain LIMITATIONS associated with Histopathology, such as:

a. Invasive: Biopsy-incisive or excisional involves cutting into the tissue, at times from multiple sites.

b. Time-consuming: starting with blood parameters to biopsy to lab procedure, and finally reading the prepared slide involves various steps, procedures, and equipment, making it lengthy.

c. Expensive: Since these procedures cost a lot, therefore, though histopathology is considered the gold standard in the diagnosis of jaw lesions, there is a need to find alternative methods of diagnosis that are less invasive, inexpensive, and less time-consuming.[6]

NEED FOR ADJUNCTIVE DIAGNOSTIC TOOLS

Options for non-invasive methods are in demand and being explored extensively. Vital staining, use of autofluorescence, chemiluminescence, USG, imaging modalities, plain CT, CBCT, and MRI are some such techniques. With the evolution in the field of Artificial Intelligence (AI). The non-invasive methods with the help of AI can help reach a diagnosis without the need for biopsies is to be explored.

CLINICAL DECISION SUPPORT SYSTEMS (CDSSs)

The world is changing to adapt to the use of AI in the field of medicine. Though AI is known to take over many fields, in the field of medicine, it can be used as a supportive or adjunct tool rather than a replacement of physicians and doctors.

With the availability of raw data for machine learning and support of analytics under the guidance of experienced doctors, AI can help in clinical decision making, treatment planning, and progress evaluation.[7]

A type of AI is clinical decision support systems (DSS) that intelligently filters knowledge and patient information to provide diagnoses and evidence support for clinical decisions. They are aimed at assisting the physician in decision-making.[8]

HISTORY AND DEVELOPMENT OF CDSSS

Studies regarding the use of computers as a support system for professionals began as early as 1950. The first evidence for its use for medical purposes is seen in the paper 'Reasoning Foundations of Medical Diagnosis' published in the late 1950s by Ledly and Lusted. This opened a gateway for more exploration along the road.[9]

They reported that diseases and their manifestations can be linked using punch cards. The resistance to accept something not part of medical education and the inadequacies of knowledge of the field of computers acted as a hurdle to its acceptance.

F.T. de Dombal et al. studied the diagnostic process using Bayesian probability theory to develop their system, the Leeds abdominal pain system. The Pathfinder system for the diagnosis of lymph node pathology was also made on similar basics.[10]

MYCIN8, the first rule-based system, was developed in 1970. It further led to more systems based on a similar model.[11]

Hybrid systems now combine deductive rules and probabilistic reasoning in the same CDSS. Best known of the hybrid systems are the general medical consultation systems QMR11 (1985), DXplain12 (1986), and Iliad13 (1987).[10]

The 2010s saw a surge in AI and machine learning (ML) techniques, which improved the development of CDSSs. Examples include IBM Watson Health and Google's DeepMind, which have demonstrated the potential of AI and ML in transforming healthcare decision-making.[9]

In the era of mobile and Telemedicine, CDSSs have risen beyond the culture of traditional one-to- one clinical consultations. Mobile health (mHealth) applications and remote monitoring tools have incorporated CDSSs to help patients and medical practitioners outside the clinical setup, making it more accessible and time-saving.[9]

CDSSs are being trained to include patients' preferred treatment options, making practitioners understand patients' needs and plan treatment accordingly. Ruland et al. observed that practitioners were able to provide better patient-centered treatment plans if patients' symptoms and preferences were taken into account.[10]

CDSS use in dental clinics has been recommended to be classified into either static or dynamic. Static systems are unable to upgrade in terms of new information, whereas dynamic systems can do so. Since dynamic systems have machine learning features, they can support a real-time, individualized plan by taking into account the profile of each patient.[8]

To understand this better, let us assume a patient reported to the clinic with the chief complaint of a toothache and filled out a questionnaire provided by the CDSS. The system will itself generate a treatment plan based on the information provided, which can include symptoms, dietary habits, fluoride exposure, and past dental history etc. This can help dentists include all relevant information, not overlook any option, and provide better individualized patient care.[12]

TYPES OF CDSSS

CDSS, as artificial intelligence (AI), help support clinical decision making. The two main categories of AI uses in CDSS are usually noted:

a) Knowledge-based AI (also called rules-based expert systems) and

b) Data-driven AI.

Initial systems are the knowledge-based AI ones, which mimic human decision making by using rules laid by field experts in the medical field in software terms. Rules such as in case a patient reports symptoms A, use medication B. Thus, such logic can be easily traced to its origin and reassessed.[13]

Data-driven AI has come up in the recent decade. It uses machine learning algorithms to draw patterns from huge raw data. Training datasets containing data from patient records previously treated by practitioners are fed to the system as part of training it. The CDSS thus learns to recognize or track a pattern that best fits with the best health outcome or treatment plan. On entering a new case into the system, the system uses a learned pattern to recognize and diagnose.[13]

However, based on large data sets employed as a 'training set', the data-driven AI can predict subtle changes and catch minute details, but unlike knowledge-based AI, the decision given cannot be easily tweaked and evaluated. This makes their reliability and accountability questionable.[13]

BENEFITS OF AI IN MEDICAL FIELD

1. Time saving

2. Using all the available information logically to provide the most probable diagnosis.

3. Procedures can be detailed, standardized and reproducible.[12]

4. Early recognition of certain diseases without overlooking any possibility

5. Clinical organization: Provides regular reminders, advises on cautions, keeps and maintains records. Improve work-flow.[14]

6. Non Invasive

ORAD III

DEVELOPMENT BACKGROUND

Dr. White, UCLA, developed a system named "ORAD" (https:// www. orad. org/) in 1995, based on probabilistic/ Bayesian calculations using conditional probabilities - the odds that a particular pathology would have a specific imaging feature and the prevalence of the pathology in the target population.[15]

This system has been upgraded to ORADIII and it provides a differential diagnosis to identify intra-bony lesions. A user has to put the patient's clinical and radiographic features into the system, and a list of differential diagnoses is generated by it.[16] It is very useful as an adjunct for the general dentist in diagnosing oral pathologies.[8]

As per White since there is a wide variety of lesions that may have radiographic manifestations in the jaws. Often, these lesions are difficult to interpret because their radiographic manifestations are not pathognomonic, but rather the features of one lesion are shared by others as well. Accordingly, the purpose of developing ORAD was to develop a program to assist the dentist to formulate differential diagnoses for radiographic lesions in the jaws at the same time was emphasized that it should not be used as a substitute for clinical judgement: rather only as an aid to the clinician in suggesting conditions not previously considered.[17]

A clinician using ORAD might think of it as a consulting system. A list of conditions is generated that reflects the signs and symptoms entered and may serve to stimulate the clinician to consider those that might not have otherwise come to mind. Accordingly, the value of programs such as this may be to help the clinician think broadly and to consider a wider range of possibilities when evaluating radiographic lesions. Most human errors in differential diagnosis result from errors of omission.[17]

DESCRIPTION OF ORAD III

Input parameters[17]

Includes 16 questions, with options provided, to be answered from the options provided, based on patient's clinical and radiographic features.

Patient characteristics

o How old is patient?

o What is the patient's gender?

o Does the patient have pain or paraesthesia?

Location of lesion

o the lesion origin

o Where is the lesion?

o Where is the lesion located?

o Is the lesion odontogenic in origin?

Lesion growth

o How many lesions are there?

o How big is the lesion?

o Is there bony expansion?

o Is the lesion loculated?

o the lesion borders?

o the lesion contents?

o Is there root resorption?

o Is there tooth displacement or impaction?

Output format

List of probability based differential diagnosis in order from most likely with probability percent to least likely based on the features fed to it.

ORAD DDX

DEVELOPMENT BACKGROUND AND DESCRIPTION

Enhanced diagnostic features

ORAD DDx (https://www.dentistry.nus.edu.sg/orad-ddx/) was developed at the National University of Singapore using information about lesion features from a textbook, "Oral Radiology: Principles and Interpretation".[1] It is a logical/deductive system based on an analytic/System 2 approach that produces a list of possible differentials based on inputs/ filters (radiographic features) that users select and presents a forward reasoning framework on the users. Makers claim this would result in improved diagnostic accuracy.[15]

Filters options are

• Internal density (Radiolucent/Mixed/Radiopaque)

• Border definition (Well-defined/Ill-defined)

• Border cortication (Yes/No)

• Encapsulation within soft tissue border or PDL space (Yes/No)

• Association with a single tooth periapex (Yes/No)

• Number (Single/Multiple).

GAPS IN EXISTING LITERATURE ON JAW LESIONS AND DENTAL APPLICATIONS OF CDSSS

a. Lack of Direct Validation with Histopathology

1. While Clinical Decision Support Systems (CDSSs) are emerging in dental radiology, very few studies compare CDSS diagnoses of jaw lesions directly with histopathological gold standards.

2. Most current systems assist in preliminary diagnosis but lack validation through biopsy or histopathological reports, which limits their clinical reliability. Nafees et al. noted in oncology CDSS review that head and neck tumors have less robust decision support systems compared to other cancers.[19]

b. Small Sample Sizes and Lack of Multicenter Studies: Many available studies involve small, single center datasets, reducing the generalizability of findings. There is a need for multicenter, multi-population datasets to validate the diagnostic accuracy across diverse clinical settings.

c. Absence of Prospective Clinical Trials: To date, most evaluations of CDSSs for dental applications are retrospective. There is a lack of prospective clinical trials that assess how CDSS usage influences real-time decision-making and treatment outcomes in dental and maxillofacial practice.

d. Underrepresentation of Oral Radiologists in System Development: Most CDSSs are developed by engineers or computer scientists, with limited involvement of oral radiologists during algorithm training and validation. This can lead to systems that miss the subtlety of clinical-radiological correlation that specialists are trained to recognize.

e. Inconsistent Reporting Standards: Publications often lack standardized performance metrics like sensitivity, specificity, AUC (Area Under Curve), PPV, and NPV specific to jaw lesions. Reporting methods vary, making comparisons between studies difficult.

Table 1. **Previous Studies and Validations**

Author (s) & Year	CDSS / Model Name	Type of Study	Sample / Dataset Characte ristics	Reference Standard	Performa nce Metrics	Key Findings	Reported Limitations
White SC[17]	Comput er-aided different ial diagnosi s of oral ra- diogra phic lesions	Develop mental and vali- datio n study	Radiogra phic cases represent ing a variety of jaw lesions	Confirmed Di- agnosis	Not quantitati vely re- ported (qualitati ve as- sessme nt of diagnosti c performa nce)	Demons trated fea- sibility of using com- puter-based systems to assist in radiogra phic different ial di- agnosis	Limited by small dataset and ab- sence of statisti- cal performance metric
Simeos et al.[18]	ORAD	Diagnos- tic valid- ity study	Radiogra phic cases of jaw bone pathologi es	Histopatho logical diag- nosis	67% of ORAD's diagno- ses did not match histo- path ology (approx. ac- curacy 33%)	ORAD demonst rated potential as an ad- juncti ve diagnost icaid but lacked suf- ficien t accuracy to replace clinician judg- ment	Limited data- set; no sensitivity/ specificity break- down; dependent on image quality
Brooks et al.[18]	ORAD III	Case se- ries	Five radiogra phic cases of bony jaw lesions	Expert radio- graphic inter- pretati on	Not quantitati vely re- ported	Accuracy of ORAD III was depende nt on precision and complet eness of input data	Small sample size; qualitative assess- ment only
Vicari et al.[18]	ORAD	Compara tive study with spe- cialist s	Panoram ic radio- graphs interpret ed by ORAD and dental specialists	Expert clinical diagnosis	Sensitivit y: ORAD = 87.5%; Specialists= 93.75%	ORAD perform ed compara bly to specialis ts when patholog y presence was certain	Limited sample and pathology range; specificity not reported
Kho et al.[15]	ORAD DDx (vs. Ra- diogr aphic Atlas)	Educatio nal vali- dation study	99 third- year dental students, pre-test & post- test on 8 types of radiogra phic lesions	Compariso n to expert- derived key diagnoses	The Atlas group improve d diagnosti c accuracy more than ORAD DDx (estimate d marginal mean differenc e = 1.88; 95% CI 0.30–3.46; p = 0.014; Cohen's d =0.714) (PubMed)Also, the Atlas group outperformed the Control group in recall of radiogra phic features (difference = 3.42; 95% CI 0.85–5.99; p = 0.005; Cohen's d = 0.793) (PubMed) Students re- ported that both ORAD DDx and the Atlas in- creased their confidence and decrease d mental effort (p ≤ 0.001)	The non-analytic Atlas approach was more effective in improvi ng diagnost ic accu- racy and feature re- call than the analytic CDSS (ORAD DDx) among student users. Both aids increase d confidence and re- duced cognitive load.	Context limited to undergraduate dental students; not a clinical di- agnostic perfor- mance study; un- known how results translate to prac- ticing clinicians.
Kalambe et al.[18]	ORAD II	Cross- sectional comparat ive study	Radiogra phic im- ages of benign jaw lesions as- sessed by ORAD and maxillof acial radiologists	Histopatho logy	Diagnost ic accuracy: ORAD =50%; Radiologists = 68.4%; p = 0.103 (not signifi- cant)	No significant differ- ence in diagnost ic accuracy between ORAD and radiolog ists; AI tool showed potential as an ad- juncti ve diagnostic aid	Limited to benign lesions; moder- ate sample size; single-center data

AI systems for histopathology are mainly developed for general cancer pathology, with minimal focus on oral/maxillofacial pathology. Ben Khalfallah et al. reviewed CDSSs in healthcare, identified that dental and maxillofacial applications are "emerging" but "understudied".[20]

Large scale studies preferably prospective and Clinical Trials are needed for assessing and authenticating various AI tools including CDSSs. The 2013 SPIRIT (Standard Protocol Items: Recommendations for Interventional Trials) statement which offers evidence-based guidance for clinical trial reporting encourages trial on AI via its extension SPIRIT-AI.[21] This 15 point checklist will not only help researchers, product makers, promoters to come up with standardized and quality innovations in the field of Health and Medicine but also provide a unified evaluation of researches in the field of AI which is not yet widely understood or accepted.[22]

CONCLUSION

With the changing times, the field of Health, Medicine and Dentistry need to adapt technology and innovations pertaining not only to instruments and materials but Artificial Intelligence as well. Though gold standards such as histopathology have a long way to go. The support provided by CDSSs should be explored and used as an adjunct in patient treatment/care or as teaching aid. Clinical Decision Support Systems (CDSSs) such as ORAD III and ORAD DDx, which have been developed and researched, should be implemented in clinical settings in accordance with evidence- based practice.

The way forward should be being aware of and updated to innovations and researches going on in the field of AI elsewhere in the world, and after evaluation and modifications following local research, put them to use. To do so the policymakers, health care providers (public and private) and universities need to stay up-to-date with global development in this field.

Another would be for the country to utilize its own experts and resources available to come up with innovations in the field of AI in Healthcare and Medicine.

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